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Towards Smarter Infrastructure: Integrating CS and AI-Driven Edge IoT Systems

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Abstract

Compressive Sensing (CS) has emerged as a modern and alternative signal processing paradigm that challenges the traditional Nyquist-Shannon sampling theorem by enabling accurate signal reconstruction from significantly fewer measurements. This paradigm proves particularly valuable in edge-enabled IoT systems, where devices operate under strict constraints in terms of energy, bandwidth, and computational capacity. In this article, we explore the application of CS in edge-enabled IoT scenarios, with a focus on smart infrastructure monitoring. We examine various system architectures and frameworks that leverage AI-based solutions to optimize resource utilization while maintaining high levels of accuracy. However, the mere integration of CS or AI models does not inherently ensure optimal performance. Achieving tangible benefits requires careful co-optimization of communication and computation strategies at the edge, in order to fully harness the energy-saving potential of these technologies in real-world IoT deployments. To this end, the article presents a range of strategies designed to address this challenge, highlighting the effectiveness of combining CS and AI in edge IoT systems and paving the way for more efficient and intelligent resource management in AI-empowered IoT environments.

I. Introduction

Compressive sensing (CS) is a modern signal acquisition framework that enables the recovery of high-dimensional signals from a reduced set of measurements, provided the signal exhibits some degree of sparsity or compressibility in an appropriate domain. This breakthrough departs from conventional sampling strategies dictated by the Nyquist-Shannon theorem, offering a more efficient approach to data acquisition by directly capturing the most relevant information. In doing so, CS not only alleviates the burdens of data storage and transmission but also significantly reduces energy consumption, a benefit of paramount importance in scenarios involving battery-powered or energy-harvesting devices. The implications of compressive sensing are particularly promising in applications requiring continuous and real-time monitoring, such as structural health monitoring (SHM), where large volumes of accelerometric data are collected over extended time frames. In such contexts, traditional sensing techniques can become impractical due to the high costs associated with data acquisition, processing, and transmission. CS addresses these challenges by enabling the efficient capture of essential dynamic information with fewer sensors or lower sampling rates, without compromising the integrity of the reconstructed signals. This efficiency proves especially advantageous in embedded systems and wireless sensor networks deployed in civil engineering scenarios, where lightweight, low-power, and autonomous operation is essential. The fusion of CS with real-time monitoring frameworks allows for smarter, scalable sensing architectures capable of early anomaly detection, system identification, and long-term diagnostics, thereby extending the operational lifespan and safety of critical assets. As the Internet of Things continues to evolve in tandem with advances in AI, a new class of intelligent, distributed sensing systems is emerging, capable of addressing the complex demands of applications such as structural health monitoring. In this context, we leverage deep learning not only as an alternative to traditional compressive sensing reconstruction but also to enable autonomous decision-making at the edge. This convergence allows for hybrid architectures that flexibly balance centralized and decentralized processing, depending on the operational scenario and resource availability. By embedding AI capabilities into edge devices, we reduce latency, improve energy efficiency, and facilitate timely responses to critical events. Ultimately, this co-evolution of IoT and AI supports the development of robust, adaptive, and scalable monitoring frameworks that align with the goals of long-term sustainability and safety in civil infrastructure systems, as well as that of many other IoT applications.

In this context, this article provides a system-level perspective on the joint use of compressive sensing and AI-based techniques for edge-enabled structural monitoring. The key insight is that neither CS nor AI alone is sufficient to guarantee optimal performance in realistic IoT deployments. Instead, effective solutions emerge from the co-design of sensing, compression, communication, and edge intelligence strategies, which must be jointly adapted to signal characteristics

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and network conditions. This work highlights how such integrated approaches enable more efficient and robust monitoring systems, offering practical guidelines for balancing energy consumption and reconstruction quality in real-world scenarios.

II. State of the Art

Compressive sensing (CS) challenges the traditional boundaries imposed by the Nyquist-Shannon sampling theorem, enabling the accurate reconstruction of signals from far fewer measurements than previously required. The theoretical underpinnings of CS have been extensively studied [1], and its concept and applied potential has been further explored in frameworks combining modern mathematical insights with practical engineering perspectives [2]. While several papers have demonstrated practical applications of CS, its potential remains vast, particularly in domains such as structural health monitoring, where the ability to compress data at the source without significant loss of information is essential for continuous, large-scale monitoring of civil infrastructures.

Thanks to its versatility, CS has been applied across many domains, including in the context of deep learning, which explores neural adaptations of the CS paradigm. For instance, [3] presents a deep neural network as a substitute for traditional CS algorithms, demonstrating how learned models can effectively replicate the behavior of CS recovery while potentially offering enhanced adaptability. [4] introduces RACSNet, a rate-adaptive neural network that allocates block-wise sampling rates based on reconstruction distortion without ground truth, significantly improving compressive sensing reconstruction quality, while [5] proposes an adaptive block-based compressive sensing method estimates block sparsity via dual reconstructions to optimally distribute measurements, enhancing reconstruction quality at lower sampling rates. A related comparative study, [6], systematically evaluates traditional CS approaches against autoencoder-based techniques on synthetic signals, providing insights into the respective strengths and limitations of these methods, particularly in terms of reconstruction fidelity and computational efficiency.

The capacity of CS to reduce the amount of information that needs to be transmitted aligns well with low-power wide-area network technologies such as LoRa, which is increasingly adopted for IoT deployments requiring energy-efficient, long-range communication. Within this context, [7] develops an energy-efficient scheduling method that integrates CS for data reconstruction, aiming to optimize network performance while reducing energy consumption. In a similar vein, [8] presents a dynamic allocation system that adjusts transmission parameters based on signal characteristics to maximize the signal-to-noise and signal-to-interference ratios, thereby extending coverage while preserving system throughput and transmission resources. Further, [9] investigates the energy consumption associated with different LoRa configurations, proposing a method for parameter selection that minimizes transmission power without compromising data integrity.

Building upon the authors' prior research on the application of CS to real-world infrastructure monitoring scenarios, particularly in the context of signal processing for modal analysis and civil engineering [10], this study extends the investigation toward more integrated and intelligent AI-enabled edge IoT architectures. In particular, this article investigates the use of Compressive Sensing (CS) in edge-enabled IoT scenarios, with a particular emphasis on smart infrastructure monitoring. We present and discuss several system architectures and frameworks that incorporate AI-based techniques to enhance resource efficiency while preserving high reconstruction accuracy. To this end, we propose a set of strategies that demonstrate the synergistic potential of combining CS and AI in edge IoT systems, paving the way for more intelligent and energy-aware resource management in AI-empowered environments. Specifically, we present a comparative analysis between conventional CS techniques and deep learning-based approaches, alongside a joint optimization framework inspired by the Social IoT paradigm. This integrated strategy aims to minimize energy consumption and computational overhead for both communication and processing tasks, while ensuring high-fidelity signal reconstruction at the receiver.

III. CS Theory Synopsis

Compressive Sensing (CS) is a modern sampling paradigm that allows the reconstruction of a signal from a significantly reduced number of measurements, as compared to the requirements of traditional acquisition techniques. The core strength of CS lies in its generalization capabilities, it does not depend on the type of signal being sampled, but rather on the signal's inherent sparsity or compressibility in some transform domain. This makes CS particularly suitable for a wide range of applications, including Structural Health Monitoring (SHM), where continuous sensing of vibrational signals is required for infrastructure integrity assessment. The reconstruction of a signal in the CS framework involves solving an optimization problem aimed at finding the sparsest solution that fits the observed measurements. This is typically formulated as an L_1-minimization problem.

$$\min \|\boldsymbol{x}\|_1 \quad \text{subject to} \quad \boldsymbol{Ax} = \boldsymbol{y}, \tag{1}$$

Successful recovery depends on two key principles: the sparsity (or compressibility) of the signal and the incoherence of the sensing matrix. In practice, many real-world signals are not strictly sparse but are compressible, meaning they can be well-approximated by sparse representations. This is often the case for accelerometric signals, where most of the energy is concentrated in a small number of coefficients in a suitable transform domain.

By reducing the volume of data that needs to be transmitted and stored, CS significantly lowers energy consumption, which is critical in resource-constrained environments such as wireless sensor networks and embedded SHM systems. This makes it a highly effective tool for real-time signal monitoring, anomaly detection, and data-driven diagnostics, especially in scenarios where continuous acquisition must be achieved without compromising battery life or bandwidth limitations.

IV. Compressive Sensing on Real Signals

The effectiveness of Compressive Sensing (CS) largely depends on the ratio between the number of measurements M and the original signal length N. Intuitively, a higher number of measurements improves the accuracy of signal recovery by better identifying sparse components and minimizing reconstruction artifacts. However, this comes at the cost of reduced compression efficiency and increased computational demand. Therefore, CS presents a trade-off between reconstruction quality and resource utilization, which is especially relevant in low-power, real-time applications. Furthermore, such trade-off is more apparent when signals are not really sparse, since CS recovery is still possible but requires an increased amount of samples. Due to the random nature of the measurement selection process, different sets of measurements, despite having the same size, may yield varying reconstruction performance.

Because of this, we use the term *Pseudofrequency*, with its measurement unit being *Pseudo-Hz*, to describe the average number of random measurements per second collected for CS recovery, a simple and viable strategy inspired by [11]. This term captures the quantity obtained when signal samples are acquired at nonuniform time intervals, as is typical in compressive sensing. Within this framework, pseudofrequency is consistent with the use of partial Fourier matrices in CS theory, where a subset of nonuniformly spaced samples is randomly selected to enable signal reconstruction. The quality of the recovered signal $\hat{\boldsymbol{x}}$ can be assessed through several metrics [12], such as the recovery error (RE), the root mean square error (RMSE), and compression ratio (CR). In order to better evaluate the validity of the results, in our previous works we have also used a normalized version of the RMSE, to provide a more signal-independent interpretation, as well as the cosine similarity index, to assess whether the shape of the signal is correctly maintained after CS recovery.

Together, these metrics offer a comprehensive view of CS performance across different reconstruction strategies and measurement configurations.

A. The IoT Infrastructure

In the context of infrastructure monitoring, a custom IoT node was developed in order to measure data, collect it, and process it. The node is fully self-sustaining, powered by a compact 5V solar panel that recharges its internal battery, ensuring continuous operation without external power sources. In practical deployments, the installation of such self-powered nodes must also account for infrastructure-specific constraints, including panel exposure to sunlight, accessibility for periodic maintenance, environmental degradation, and placement limitations imposed by bridges, tunnels, or other civil structures. These aspects may affect long-term energy availability and represent an important consideration for large-scale real-world adoption. Thanks to its small size, the solar panel preserves the lightweight and low-power nature of the IoT approach while enhancing node autonomy. At its core lies a Walter model ESP32, a versatile microcontroller that acquires high-resolution data from an external high-precision accelerometer, converting these analog vibrations into digital signals via an integrated ADC.

What sets this node apart is its flexible connectivity. The ESP32 Walter model not only supports Wi-Fi but also integrates 5G connectivity, enabling direct broadband access without relying on external gateways or add-on modules. This design ensures that even in remote monitoring scenarios, data can be seamlessly transmitted to the network. Additionally, the node is equipped with a LoRa module and antenna, allowing it to transmit compressed data using compressive sensing techniques when bandwidth conservation is essential. This dual-mode capability empowers the system to dynamically switch between transmission strategies depending on channel conditions, battery status, or bandwidth availability.

Beyond connectivity, the node is engineered for seamless integration with monitoring infrastructures, publishing data over HTTP with database storage and via MQTT for lightweight, real-time messaging. This interoperability also makes the proposed architecture compatible with broader digital-twin ecosystems, where real-time sensing data collected at the edge can be used to continuously update virtual representations of critical infrastructures and support higher-level monitoring services. In this sense, the proposed framework can be seen as an enabling sensing and communication layer for data-driven digital twin applications [14]. All in all, this IoT node embodies a flexible, energy-aware, and bandwidth-efficient sensing platform, ready to deliver high-quality structural health data while adapting intelligently to the demands of the environment it monitors. In this connection, Fig. 1 summarizes the main characteristics of our proposed system.

B. Applying Compressive Sensing

In exploring the use of compressive sensing for structural health monitoring, our work focused on applying this technique to real-world data gathered from a road bridge using low-cost IoT sensors. These devices, connected via Wi-Fi, continuously collected inertial signals, providing a valuable testbed for evaluating CS in conditions where signal sparsity is not guaranteed. Using well-established tools in convex optimization and sparse signal recovery, we reconstructed the signals and assessed the quality of the results under varying compression levels and algorithmic approaches. Fig. 2(a), 2(b), and 2(d) present comparisons between original and reconstructed spectra obtained using either traditional compressive sensing or its AI-driven implementation. The reconstruction quality is evaluated using normalized root mean square error (nRMSE) and cosine similarity metrics, both indicating that the recovered signals accurately preserve the shape and amplitude of the originals. Similarly, Fig. 2(c) reports nRMSE values as functions of the LoRa coding rate and the CS compression factor, illustrating the combined influence of these parameters on signal reconstruction performance.

What emerged from these experiments is a nuanced picture of CS performance in practice. Unlike idealized scenarios where signals are highly sparse, like the one shown in Fig. 2(a), which was obtained in a controlled environment from an experimental structure meant to simulate the behavior of a real one, vibrational data from a real structure, such as the analyzed bridge, can sometimes show limited sparsity in the frequency domain, both because of the structure itself as well as because of noisy measures. This constrained the effectiveness of compressive sensing under strictly sub-Nyquist sampling conditions. However, CS remained surprisingly robust even in these less-than-optimal cases.

For signals with modest sparsity, such as that shown in Fig. 2(b), it is still feasible to apply CS to reduce the number of measurements without losing essential information. While signal reconstruction metrics such as RMSE show the effectiveness of CS, achievable results are not just numerical: visual

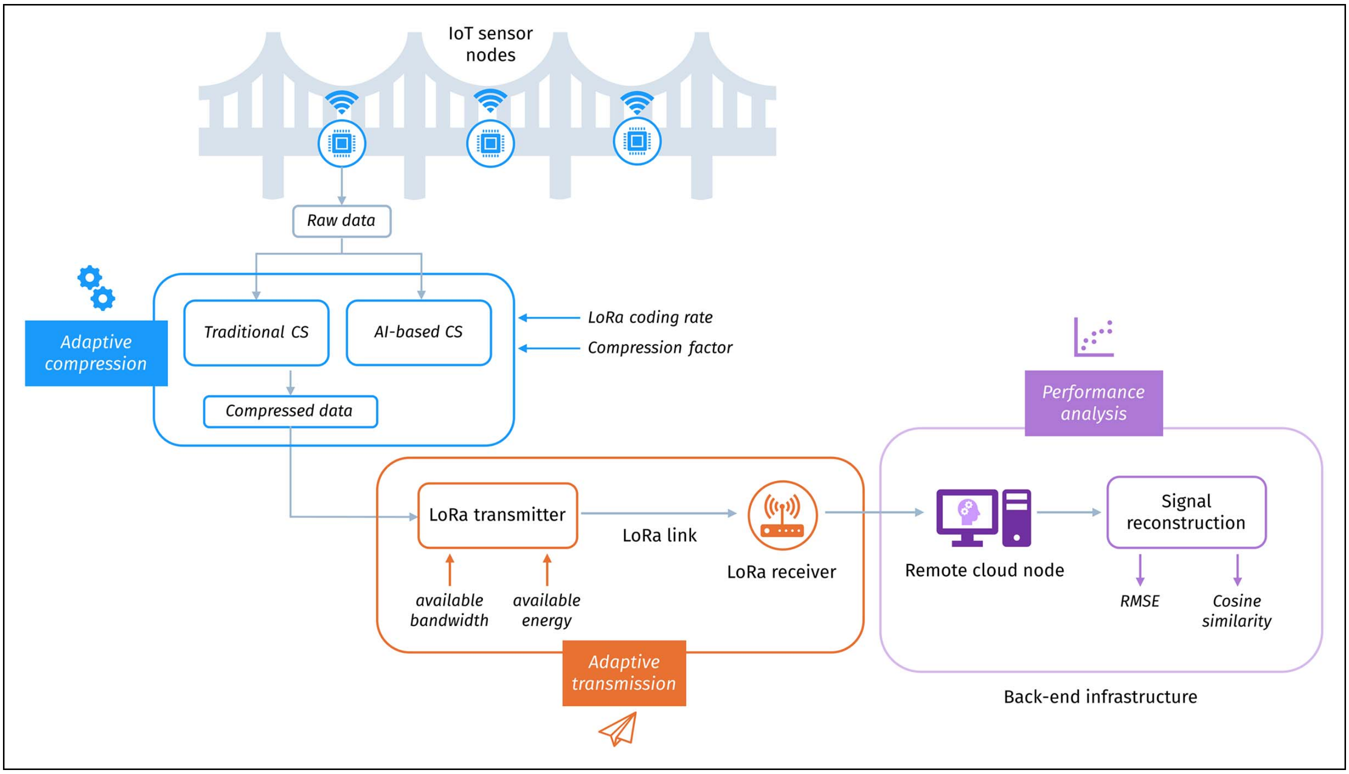


FIG. 1. General architecture of the proposed AI-enabled IoT system.

comparisons of reconstructed signals clearly show the fidelity achievable through careful compression and recovery, even in real-world, noisy environments.

An important observation concerns the choice of reconstruction algorithms. Compressive sensing can be achieved through various optimization algorithms, which differ in effectiveness and efficiency. Reweighted L_1 minimization often yields the best accuracy, but it also demands more computational time, making it more suitable for offline analysis or edge devices with sufficient processing capability. Basis Pursuit and Homotopy methods, instead, offered faster alternatives with comparable performance, especially for signals that are sufficiently sparse. For conciseness purposes, only results attained via Basis Pursuit are shown.

Ultimately, our studies demonstrated that compressive sensing, when carefully applied, can offer meaningful reductions in data volume and transmission energy, even with real signals that deviate from the ideal sparse models often assumed in theory. The experiments showed that it is possible to operate at lower sampling rates and still reconstruct usable signals, striking a balance between accuracy and efficiency. This has practical implications for the design of IoT-based monitoring systems, where bandwidth and energy constraints are paramount. By showing that CS can adapt to the limitations of low-cost sensors and real-world signal characteristics, we highlight its potential as a key enabler for future smart sensing platforms in structural health monitoring.

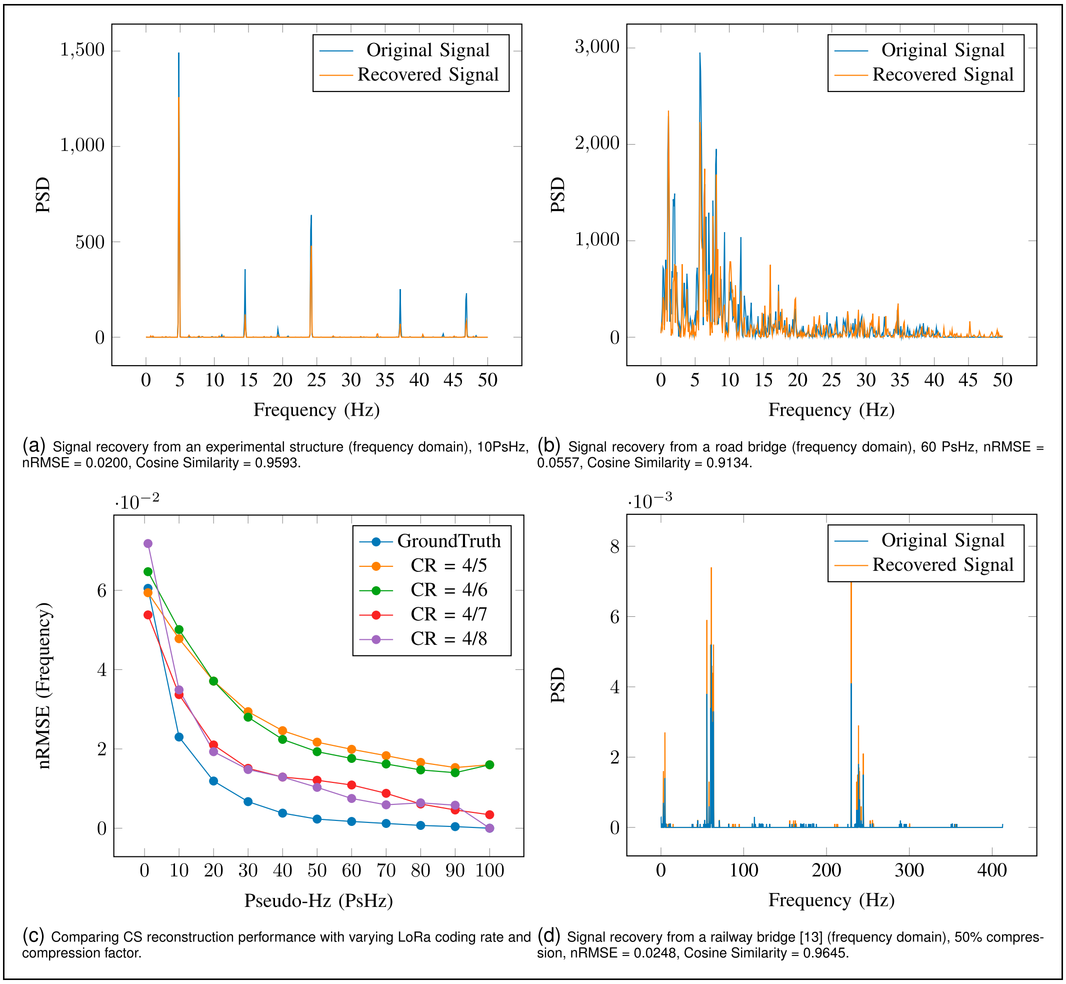
C. Social IoT

In a typical Structural Health Monitoring (SHM) scenario, multiple sensor nodes are deployed across the structure. Each node acquires local measurements and transmits them to a central processing unit or forwards them upstream for further processing. This operation inherently involves a trade-off between the energy consumption associated with data transmission and the reconstruction quality at the receiver, which determines how accurately the monitored structural response can be interpreted.

To investigate this trade-off, we developed a simulated test environment where each sensor node transmits its data under realistic conditions using LoRa, a low-power, long-range communication protocol. Within this approach, LoRa transmission parameters, such as coding rate and spreading factor, are adaptively tuned to optimize the balance between communication cost and signal fidelity. By simulating different noise levels, coding rates, spreading factors, and compression factors, we were able to observe how these choices influence both energy efficiency and reconstruction quality.

Compression plays a central role in this dynamic. By reducing the data volume to be transmitted, energy and bandwidth can be saved, but it is crucial that the essential information survives the process. Here, compressive sensing enables the reconstruction of signals even when only a fraction of the original data is transmitted. The success of this reconstruction depends on signal sparsity: highly sparse signals are easier to recover, while less sparse signals present greater challenges.

For quantification purposes, tests were conducted across a range of noise levels, using various kinds of regressors to model how reconstruction quality varies with different compression factors and coding rates. At higher noise levels, each transmitted byte becomes more susceptible to distortion but, interestingly, compressive sensing often manages to recover the original signal even under such adverse conditions. Higher coding rates generally enhance noise resilience, and as the signal-to-noise ratio improves, reconstruction quality approaches the system's



(a) Signal recovery from an experimental structure (frequency domain), 10PsHz, nRMSE = 0.0200, Cosine Similarity = 0.9593.

(b) Signal recovery from a road bridge (frequency domain), 60 PsHz, nRMSE = 0.0557, Cosine Similarity = 0.9134.

(c) Comparing CS reconstruction performance with varying LoRa coding rate and compression factor.

(d) Signal recovery from a railway bridge [13] (frequency domain), 50% compression, nRMSE = 0.0248, Cosine Similarity = 0.9645.

FIG. 2. Experimental results.

theoretical optimum. Looking at the results, an increase in compression reduces transmission energy but can degrade reconstruction quality, especially for weakly sparse signals. More robust LoRa settings improve reliability but increase transmission energy, so optimal performance requires jointly tuning compression and communication parameters. For instance, low SNR favors moderate compression with stronger LoRa settings, while favorable channels allow higher compression and lower transmission overhead. Fig. 2(c) illustrates reconstruction performance across different LoRa coding rates and compression levels, compared to baseline CS recovery obtained without channel effects.

From a Social IoT perspective, neighboring sensor nodes can also cooperate by sharing contextual information in localized monitoring scenarios. For example, if a node placed near a bridge joint detects abnormal vibration patterns, nearby nodes positioned on adjacent structural elements may temporarily increase their sampling frequency, relay redundant measurements, or prioritize data transmission to provide a richer representation of the event. This cooperative behavior improves situational awareness without requiring centralized intervention for every local anomaly.

Throughout these experiments, the system parameters were kept consistent to isolate the impact of compression and coding strategies on the trade-off between energy consumption and data quality. The resulting trends are clear: under low-noise conditions, the differences among configurations diminish, converging toward a shared, optimal reconstruction performance. This behavior underscores the robustness of compressive sensing and highlights how adaptive tuning of LoRa parameters enables high-quality data reconstruction while respecting the strict energy constraints typical of distributed sensing networks.

D. AI-Based CS Implementation

When considering a possible AI-based implementation of CS for real-world scenarios, each sensor can be equipped with a lightweight neural model capable of compressing the acquired signals into a highly compact representation before transmitting them over the network. This approach substantially reduces both bandwidth usage and energy consumption, making the overall monitoring system more efficient and less intrusive. Once data reaches the central hub, a corresponding neural model reconstructs the original signal, ensuring that no essential information is lost during transmission.

This method does more than simply compress data. It adapts to changing conditions, ensuring that the most important information is always preserved, even if the environment around the structure changes. It effectively embeds artificial intelligence capabilities directly at the edge together with classic CS methods, minimizing heavy data transfers while

	Traditional Compressive Sensing	AI-Based Compressive Sensing
Encoding approach	Random projection	Learned CNN encoder
Decoding method	Iterative algorithms	Learned CNN decoder
Underlying assumption	Sparsity in transform domain	Statistical structure learned from training data
Training requirement	None (model-agnostic)	Training on representative data
Training data amount	None	Requires large dataset
Maintenance Complexity	Very low	May require updates to adapt to new data
Reconstruction speed	Slow due to iterative optimization	Fast due to feedforward inference
Generalization	Strong especially for sparse signals	Depends on similarity to training data
Noise robustness	Good, can degrade with higher compression	Potentially higher due to learned data priors
Real-time suitability	Limited (due to reconstruction time)	Suitable for real-time applications

TABLE I. Comparison between traditional compressive sensing and AI-based compressive sensing.

maintaining high fidelity in signal recovery, a principle consistent with the broader vision of Symbiotic IoT.

To test the system's resilience and generalizability, we evaluated various neural models on heterogeneous datasets, assessing how well deep learning-based compression techniques can support structural health monitoring. At the heart of this approach lies the autoencoder, a neural network that learns to encode input data into a smaller latent space and then reconstruct it, capturing the essence of the original signal. Unlike traditional compressive sensing, which relies on mathematical sparsity and other properties, such as the coherence of the reconstruction matrix, autoencoders learn directly from data, adapting to complex signal distributions where traditional CS methods may struggle.

Taking this a step further, convolutional autoencoders incorporate convolutional layers, allowing them to capture local patterns and hierarchies within data. This makes them particularly effective for time-series signals and vibration maps.

To evaluate their effectiveness, we compared these models to compressive sensing. Whereas compressive sensing can capture a signal's frequency content using only a fraction of the usual samples, even below the Nyquist limit, it relies on the assumption of sparsity. When signals become too complex and lack clear sparsity, compressive sensing becomes less efficient, requiring more samples for accurate reconstruction. In contrast, while autoencoders might not always reach the extreme compression ratios of compressive sensing, they effectively reconstruct complex signals even when they are not sparse, as seen in our previous work [15]. Because of this, the joint CS-AI strategy enhances both efficiency and adaptability, aligning with the vision of intelligent and resource-aware structural health monitoring.

There is a clear tradeoff. Compressive sensing keeps sensors simple and energy-efficient but shifts computational demands to the data processing side and is effective mainly for sparse signals. The AI-based solution, on the other hand, requires more computational resources during training and add modest complexity at the edge but can compress a wider range of signals. This not only allows for faster processing during data acquisition but also streamlines downstream analysis, supporting the vision of intelligent, adaptive, and efficient structural health monitoring systems of the future.

An example of this is shown in Fig. 2(d), where a signal acquired from the Leuven railway bridge [13] is successfully reconstructed using a deep learning architecture inspired by compressive sensing principles. In this case, the autoencoder's latent space was set to half the size of the original signal. While the notion of pseudofrequency does not strictly apply in neural network-based compression, as the mechanism differs from the optimization-based formulation of classical CS, the effect is comparable: the model retains the spectral content of the signal despite operating on a compressed representation equivalent to using only half of the original samples. Furthermore, Table I shows a qualitative comparison recounting the main differences between the traditional CS approach and the CS-inspired deep learning approach.

V. Conclusion

This study explores the integration of compressive sensing and artificial intelligence in IoT-based Structural Health Monitoring systems, focusing on energy efficiency, signal fidelity, and adaptability. We deployed a custom solar-powered IoT node with flexible connectivity (Wi-Fi, 5G, LoRa) to demonstrate the feasibility of compressive acquisition in dynamic environments. Experiments on both synthetic and real-world vibrational data showed that traditional CS techniques, even under imperfect sparsity, can provide high-quality signal recovery while reducing energy and bandwidth needs. We also investigated AI-based methods, specifically autoencoders and convolutional autoencoders, as adaptive alternatives. These models performed well on complex, non-sparse signals, offering greater flexibility and generalizability despite higher computational demands. Additionally, we introduced a "Social IoT" approach, where sensor nodes coordinate transmission strategies based on local and network-wide conditions. Simulations with realistic noise and channel models confirmed the benefits of such collaboration in optimizing energy use and data quality. The concept of "Social IoT" is introduced here as a high-level illustration of cooperative behaviors among sensor nodes. In this paradigm, nodes may share contextual information about local measurements, channel conditions, or energy availability, which could inform adaptive choices of sensing or transmission parameters. While this paper does not implement a specific social metric or quantitative collaborative algorithm, the discussion highlights how such cooperative interactions could conceptually enhance the robustness and efficiency of distributed monitoring systems. Our results highlight CS and DL as complementary tools for building intelligent, sustainable, and scalable SHM systems.

Future work will be directed toward the development of advanced hybrid frameworks capable of dynamically selecting between compressive sensing (CS) and deep learning (DL) strategies according to real-time contextual information, such as signal sparsity, environmental conditions, and computational constraints. This adaptive approach aims at exploiting the complementary strengths of both paradigms, ensuring optimal performance under varying operational scenarios. Improving the AI-based side of this system will also be our focus, with respect to perfecting the latent representation for both transmission and recovery optimization in noisy real-world deployments. Furthermore, efforts will focus on the design of a hybrid and context-aware communication-compression framework. Specifically, we envision an adaptive decision logic capable of performing smart vertical handover between different transmission technologies (e.g., LoRa, WiFi, and 5G) while simultaneously tuning compression parameters and methods. The objective is to dynamically identify the most energy-efficient and reliable configuration based on channel conditions, signal sparsity, and data relevance, thereby optimizing both communication and data recovery processes. From an infrastructure management perspective, such a mechanism would allow operators to prioritize low-latency communication for emergency events, energy-efficient transmission for routine monitoring, and high-bandwidth connectivity for firmware updates or diagnostic operations, improving both operational flexibility and maintenance efficiency. In addition, significant efforts will be devoted to the real-time implementation of the proposed algorithms on dedicated systems, in order to thoroughly assess their efficiency, scalability, and robustness in realistic, large-scale structural monitoring deployments. At the same time, an analysis of computational and operational requirements will be carried out to provide further insight on the feasibility of this approach. These future developments are expected to bridge the gap between theoretical modeling and field applicability, ultimately advancing the state of the art in intelligent sensing and data-driven infrastructure management.

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